Aalto University
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DOES ESG PERFORMANCE INFLUENCE A FIRM'S PROBABILITY OF DEFAULT?

Forecasting default in European corporate markets using Merton's Distance-to-Default model and effects of ESG policies on the risk of default

Master's Thesis
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Abstract of master's thesis

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Abstract

This thesis investigates the effects of engagement in ESG (environmental, social, governance) activities on the probability of default by using data from 423 non-financial public European firms between 2000 and 2019. The probability of default proxy is calculated by using the structural model of Merton's distance-to-default and the measures for ESG Score and ESG Controversies score are obtained from the Refinitiv database. ESG Score is calculated by Refinitiv based on the data provided by each company and compared to peers, while ESG Controversies score is based on controversial ESG events' information collected by Refinitiv from public media.

The statistically significant results support one of the hypotheses that firms with higher ESG scores experience a higher probability of default, while either unobserved firm-related or year-related variables are being fixed. There was no significant evidence found to support the opposite hypothesis that higher ESG scores are negatively related to the probability of default. Another hypothesis that firms with higher ESG Controversies scores have a lower probability of default is also supported by the results of this thesis.

Keywords ESG, ESG policies, default, risk of default, probability of default, distance-to-default

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1. Introduction

The interest in the topic has occurred to me when the COVID-19 pandemic started having clear effects on the economy in the Summer of 2020 and a higher risk of default has become a reality for many companies. While there are established practices of determining and predicting the default by credit-issuing institutions, more accurate, up-to-date, and dynamic methods are needed for the current situation when many firms are at risk. On the other hand, ESG-reporting has become more common in the last decade and the effects of the environmental, social, and governance activities on firm performance have been studied more intensively. While there has been extensive research conducted on the CSR (corporate social responsibility) and its implications on stakeholders, E (environmental) and S (social) aspects have not been studied as much. With this paper, I aim to contribute to this research.

I came across a study performed by Baghdadi, Nguyen, and Podolski (2019), which attempted to find a connection between co-opted boards and default risk with a sample of U.S. public firms (excluding financial firms) in 1996 and 2014. Baghdadi et al. have found that co-opted boards (following the definition by Coles et al. (2014), co-opted boards are directors appointed by the CEO after assuming office) are contributing to the default risk by their erratic and arbitrary decisions. This in turn leads to higher stock return volatility and fundamental volatility in firms with co-opted boards. According to their study, the co-opted boards are not necessarily characterized by more risk-taking, but they are less involved in strategic decision-making. Some external oversight mechanisms, such as analysts or institutional investors, mitigate some of the effects documented by Baghdadi et al. (2019). This interesting relationship between the co-opted boards and the default risk would be interesting to study on the European firms if the data were regularly collected for these firms. On the other hand, ESG-scores data is available for more firms every year and it is an interesting variable to look at in relation to default risk. According to my knowledge, there has not previously been a similar study performed for European firms for the time when more ESG-data has been available for most of the firms and therefore I would like to contribute to closing this gap with my research paper.

The research question is as follows:

What is the effect of the ESG policies on the default risk: do higher ESG-scores make the firms' probability of default higher or do they reduce the risk based on the dataset from European corporate markets in 2000-2019?

Some of the existing literature suggests that ESG-activities can be beneficial for the firm's ability to meet its debt obligations, as such activities are positively linked to the firm's financial performance. On the other hand, several authors point out that ESG can become a way for the management to build reputation, while not paying enough attention to the value-optimization of the firm. These different positions create a possibility for opposite effects ESG-activities may have on a probability of default – increase or decrease it. As a result, the opposite answers to my research question are equally possible.

Hypothesis 1 - the higher ESG-activities increase the default probability of a firm.

This hypothesis is in line with the agency theory, which has been suggested as an explanation of higher CSR activity by Rizwan, Obaid, & Ashraf (2017) and higher ESG-activity by Dorfleitner, Kreuzer & Sparrer (2020). Both studies suggest that it is possible for CSR or ESG-activity to negatively affect the firm's performance, and therefore increase the default risk, since managers seek personal benefits, such as public recognition, by engaging in the ESG-activity, while the shareholder value decreases, and the financial performance is poor. The investments in the ESG-activities may not be optimal for the firm's financial performance, therefore agency problem occurs.

Dorfleitner et al (2020) presented several views on why higher ESG-activity could be positively influencing financial performance. They point out that it is possible when the costs associated with the ESG-activities are overestimated or when the benefits from such activities exceed expectations. This is supported by Dorfleitner et al.'s (2018) findings that higher socially responsible activities can be linked to unexpected additional cash-flows in the mid- or long-term. And while Rizwan et al.z (2017) use different methods of defining the levels of the ESG-activity, they also find evidence that higher ESG-scores are linked to a lower probability of default. This view could help clarify the results if they do not support my first hypothesis.

In parallel, I am checking the effects of the ESG Controversies score on the default probability. The data on the ESG Controversies scores is easily retrievable together with the ESG scores since these two measures are often registered at the same time. The higher the score for both the ESG score and for the ESG Controversies score, the better the company has performed through their ESG activities and in terms of working with controversies. For ESG Controversies score calculation, Refinitiv identifies 23 controversy topics and collects data from the global media (Refinitiv, 2021).

Dorfleitner et al. (2020) suggested that providing the ESG Controversies information reduces the inefficiency of the market. They point out that ESG-scandals cause public attention and are immediately priced, while the absence of the scandals leave such firms' activity unnoticed and even overlooked. It is also noted by them that the ESG Controversies scores are comparable to the credit default scores since they both evaluate the absence of an infrequent event. With these findings in mind, I find it reasonable to propose the second hypothesis:

> Hypothesis 2 – the ESG Controversies scores are negatively related to the probability of default.

As previously explained regarding ESG scores and their relation to the probability of default, the opposite outcomes of the investigation of the relation between ESG Controversies scores and the probability of default are also possible.

It is worth mentioning that endogeneity concerns can be present in terms of understanding casual relationships between ESG activities and the probability of default. Baghdadi et al. (2019) raise this issue in their study and address it with the data available regarding co-opted boards. Soytas et al. (2019) discuss in their paper endogeneity concerns in the relationship between sustainability and financial performance. They highlight that there is a pitfall in the ways to address the endogeneity in the previous research. Soytas et al. suggest possible sources of endogeneity being a firm's unobserved productivity level and the marginal cost of sustainability. Their results show that sustainability activities are more expensive for more productive firms (i.e. with highly efficient processes), which in turn may lead to a downward bias in OLS-estimations. Another potential source of endogeneity pointed out by Soytas et al. is the comparative advantage bias. They argue that firms with a higher ratio of financial returns to sustainability investments are more incentivized to undertake the sustainability initiatives. The authors conclude with their results that productivity bias dominates comparative advantage bias.

The rest of the paper is organized as follows. I next present an overview of the current literature, followed by the data and methodology presented in the section after that. I present the results in the “Results” section, after which the “Conclusion” concludes the thesis and presents limitations of this research as well as possibilities for further research.

2. Literature review

The current interest in ESG-investing generated an overwhelming amount of research. Friede et al. (2015) have made a comprehensive review of the research related to ESG and corporate financial performance (CFP) – a combination of findings from 2200 individual studies. Friede et al. view corporate financial performance measures as accounting-based performance, market-based performance, operational performance, perceptual performance, growth metrics, risk measures, and the performance of ESG-portfolios. This review supports the notion of the popularity of the research about ESG as well as it touches upon some measures impacting the default risk, which makes it interesting for me to investigate the patterns as well as the gaps in the research.

Friede et al. use two-step method – vote-count studies (analyzing the category of the results and “voting” the winners) and meta-analyses (econometric review studies). However, acknowledging that the knowledge regarding the topic is fragmented, Friede et al. (2015) take notice that most studies they review in their work state a positive finding (90% of the studies find non-negative relation between ESG and CFP). The positive effect of the ESG is believed to be stable over time as well. Most of the studies analyze the ESG effects on CFP in equities (87,1% in vote-count sample). ESG pillars-wise, the positive effect of E, S, and G on corporate financial performance is divided relatively even between the pillars. 62,3% of the vote-count studies point at positive effect related to the G (governance), 58,7% - in relation to E (environmental) and 55,1% in relation to S (social). Most of the negative findings are related to G (9,2%), compared to other pillars (4,3% to E and 5,1% to S). The study also analyses the findings across different parts of the world. The two main patterns Friede et al. point out: first, developed markets, excluding North America, exhibit a smaller share of positive results (e.g. in developed Europe only 27,8%

of studies find positive relations between ESG and CFP), and second, emerging markets show a considerably higher proportion of positive outcomes (65,4%). The authors note that most studies are performed on portfolios, which potentially includes a bias. After excluding portfolio studies, the share of the positive findings increases in both developed and emerging countries. These results make it clear that trends in ESG-effects cannot be applied universally across geographics, neither it cannot be assumed that they always relate positively to financial performance. My study is non-portfolio and is focusing on the European market, which is less studied than North American.

Different results have been shown by Bannier, Bofinger, and Rock (2019), who test a portfolio of U.S. and European stocks with long in stocks with highest ESG scores and short in stocks with the lowest ESG scores. Their study showed that stocks with the highest ESG scores showed negative abnormal returns, while the stocks with the low ESG scores were trading at a premium. ESG activities are seen as a way of insurance, which in turn means that the firms with low ESG activities are carrying more risk. The authors also conclude that different market phases affect whether ESG is perceived as insurance to less or more extent. Viewing ESG activities as a way of insurance would not support my first hypothesis, but could support the opposite - ESG activities could be negatively related to the probability of default.

CSR (corporate social responsibility) is an aspect of ESG, which has been monitored closely as more firms have been reporting on it. It is focusing on the firm’s relationships with the stakeholders and therefore the researchers are interested in whether it may affect the performance of the firm or its risk among other things. The CSR activities' effect on the financial performance of the firms has been studied by Goss and Roberts (2011) or Wu and Shen (2013). The way CSR affects the firm’s risk has been investigated in several studies (Benlemlih and Girerd-Potin (2014); Jo & Na (2012); Oikonomou, Brammer, Brooks and, Pavelin (2012). Similar to how ESG-activities, in general, might be perceived as a way of insurance for a firm’s cash flows, CSR is mentioned to be viewed as insurance-like protection (Godfrey, 2015). Badayi, Matemilola, N and Wei, 2020 point out in their paper that the influence of CSR on the probability of default has not been studied enough, and their research attempts to contribute to that topic. They studied the effect of CSR on the probability of default in developing countries between 2010-2017. The results of their paper suggest that with the increase of CSR activities among the firms in developing countries, the probability of default decreases. One of the objectives of my research is to see whether the same effect can be found in European countries, however, I investigated the ESG activities as a whole, not only CSR. As can be seen further in my literature review, these terms sometimes are replaced by each other, or ESG-score is taken as a proxy for CSR.

In addition to studying the effect of CSR on financial risk (Benlemlih and Girerd-Potin, 2014), Benlemlih studies how environmental and social disclosures affect a firm's risk (Benlemlih, Shaukat, Qiu, et al., 2018). They find that disclosure of such information reduces idiosyncratic and total risk, but not systematic risk. One explanation offered by Benlemlih et al. (2018) is that firms disclosing their environmental and social information are more transparent and therefore can build a more positive reputation and trust among stakeholders. Besides the main objective of Benlemlih et al.'s (2018) research, they touch upon an issue of whether extensive disclosures (in their case on E and S) are linked to superior performance in these areas. For my research, I consider ESG scores and ESG Controversies scores and the major difference between these two measures, that only ESG score is based on the disclosures by the company. ESG Controversies score is based on the events revealed by the media related to controversial ESG activities. Therefore, it will not be surprising if the relations of these two measures with the probability of default are different.

The uncertainty lies within knowing whether higher ESG-scores reflect the better ESG-performance. Benlemlih et al. (2018) point out that there are certain circumstances when investors, firms, or managers of the firms benefit from providing objective disclosures (i.e., reflecting truthful information regarding E and S activities). These circumstances are 1) reduced asymmetric information helping investors make their investment decisions, 2) regulations in these areas making firms issue objective disclosures, 3) benefits of objective disclosures exceeding their costs, 4) objective disclosures bringing corporate benefits such as reducing implied cost of capital and higher market values. Providing extensive disclosures contributes to these benefits as well.

Few authors studied the relation of the CSR/ESG-activity and the probability of default, which is directly related to my research and therefore I am interested to compare the methods and the results of the research. In 2020, Badayi et al. published a study of the firms from 17 developing countries. They found that high CSR (ESG score from Thomson Reuters Datastream is used as a proxy in their study) participation is related negatively to the probability of default in developing countries, however, this hypothesis did not hold in the African and Middle Eastern region. The main explanation of the results lies within the fact that improved CSR performance positively affects customer satisfaction and thus cash flows increase, which in turn makes the probability of defaulting on the debt obligations smaller. They also refer to the stakeholder theory and studies where it is shown that being active in CSR improves relationships with stakeholders by maximizing their wealth (Jiraporn et al, 2014), which in turn helps improve stock valuations (Jiao, 2010) and lower the cost of financing (El Ghoul et al., 2011). The stakeholder theory and the connection between the higher ESG activities and improved cash-flows could be a possible explanation to the opposite of my hypothesis – a higher ESG score is negatively related to the probability of default.

Another study, conducted by Rizwan et al. (2017), contributes to the research of the relation between CSR activities and probability of default, which is used as a proxy for the credit risk. They studied U.S. firms and found that their evidence does not support the agency theory but is in favor of the wealth protection function of CSR. Rizwan et al. (2017) split the scores into the technical (primary stakeholders related) and institutional (secondary stakeholders related) and find that technical CSR negatively affects the credit risk, while institutional CSR has insignificant relationships with the credit risk. This study also used a different measure of the CSR activities – data from the KLD research and analytics database, which has 13 dimensions of CSR, and the companies receive strength or weaknesses scores in each of the dimensions. This paper offers explanations for both outcomes – negative and positive relation of the ESG activities to the probability of default. On the one hand, the negative effect of the ESG activities on the default risk can be explained by the wealth protection function of the ESG (similar to the insurance view) – which would support the opposite explanation for my first hypothesis. On the other hand, the agency theory can explain if the ESG activities increase the probability of default, meaning that the managers use the ESG activities as the way to improve their reputation, but do not care about the stakeholders' wealth – this could be a possible explanation to support my first hypothesis. Rizwan et al. (2017) address endogeneity by using the GMM-estimator (Generalized-Method-of-Moments), developed by Arellano and Bond (1991).

3. Data and methodology

The sample consists of the firm data on 423 public European firms during 2000 and 2019 from Thomson Reuters/Refinitiv database. Following Baghdadi et al. (2019) and other authors, the financial firms were excluded from the sample. The data needed for calculating the EDF was available for the entire sample without missing values. However, I needed data for ESG scores, ESG controversies, and some fundamental data for control variables, where not all these values were available for all the firms or all years. Therefore, I performed the regressions on an unbalanced sample.

The following part of the paper discusses the methods used in my research:

1) Defining default risk by using the Merton DD (distance-to-default) model;
2) Regression on the association between ESG and default risk.

3.1 Merton's distance-to-default model

Badghdadi et al. (2019) use the Merton distance-to-default (Merton DD) model, which had been earlier described and tested in the study done by Bharath and Shumway (2008). The model is also earlier discussed in Duffie and Singleton (2003) and Saunders and Allen (2002). It is applied by Vassalou and Xing (2004); Duffie, Saita, and Wang (2007); and Campbell, Hilscher, and Szilagyi (2007), among others. The model was first suggested by Merton (1974) and developed by the proprietors of the KMV corporation.

Under the model, the firm's equity is a call option on the underlying value of the firm with the strike price equal to the face value of the firm's debt. Underlying value and its volatility are not observable but can be inferred from the value of equity, its volatility, and some other observable variables. (Bharath and Shumway, 2008)

After inferring these values, the model specifies that the probability of default is the normal cumulative density function of a *z*-score depending on 1) the firm's underlying value, 2) the firm's volatility, and 3) the face value of the firm's debt.

The Merton DD model subtracts the face value of the firm's debt from an estimate of the market value of the firm and then divides this difference by an estimate of the volatility of the firm (scaled to reflect the horizon of the forecast). Result – z-score, or distance to default (DD).

Z-score is then substituted into a cumulative density function to calculate the probability that the value of the firm will be less than the face value of debt at the forecasting horizon. The first step in implementing the Merton DD model is to estimate σ_E (stock volatility) from either historical stock returns data or from option-implied volatility data. The second step is to choose a forecasting horizon and a measure of the face value of the firm's debt. For example, it is common to use historical returns data to estimate σ_E, assume a forecasting horizon of 1 year ($T = 1$), and take the book value of the firm's total liabilities to be the face value of the firm's debt or calculate the face value of debt by adding short-term debt and half of the long-term debt. The third step is to collect values of the risk-free rate and the market equity of the firm. After performing these three steps, all values are available for each of the variables in Equations:

$$E=VN(d_1)-e^{-rT}FN(d_2)$$

and

$$\sigma_E=(V/E)N(d_1)\sigma_V$$

except for V and σ_V, the total value of the firm and the volatility of firm value, respectively. After solving the above-mentioned equations numerically for V and σ_V, one can proceed to the distance to default DD:

$$DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}},$$

where μ is an estimate of the expected annual return of the firm's assets. And:

$$\pi_{\text{Merton}} = \mathcal{N}\left(-\left(\frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right)\right) = \mathcal{N}(-DD).$$

Baghdadi et al. (2019) use the modified version of the Merton (1974) structural distance-to-default model to measure default risk in their research, which I am using in my research as well. They calculate the risk of default (EDF) the following way:

$$DD_{i,t} = \frac{ln\left(\frac{Equity_{i,t}+Debt_{i,t}}{Debt}\right)+(r_{i,t-1}-0,5\sigma^2_{V_{i,t}})}{\sigma_{V_{i,t}}}$$

$$\sigma_{V_{i,t}} = \frac{Equity_{i,t}}{Equity_{i,t}+Debt_{i,t}} \text{ x } \sigma_{E_{i,t}} + \frac{Debt_{i,t}}{Equity_{i,t}+Debt_{i,t}} \text{ x } (0,05 + 0,25 \text{ x } \sigma_{E_{i,t}})$$

$$EDF_{i,t} = N(-DD_{i,t})$$

where $Equity_{i,t}$ is the market value of equity and $Debt_{i,t}$ is the face value of debt, calculated as the sum of the short-term debt and half of the long-term debt. $r_{i,t-1}$ is firm *i*'s past annual return, calculated from monthly stock returns over the previous year. $\sigma_{E_{i,t}}$, is the annualized stock volatility for firm *i* during year *t* estimated from the monthly stock return over the previous year. $\sigma_{V_{i,t}}$, is an approximation of the volatility of firm *i*'s assets. N(.) is the cumulative standard normal distribution function.

3.2 Regression and ESG measures

Further, Baghdadi et al. (2019) use the portion of co-opted board members as the main measure of the co-option. I use the ESG-score as the main independent variable.

Baghdadi et al. (2019) estimate the following regression with standard errors corrected for heterogeneity and firm-level clustering:

$$EDF_{it} = \alpha + \beta_1 Co\text{-}option_{it-1} + \beta_2 Z_{it-1} + \varepsilon_i + \delta_t$$

where *i* and *t* refer to firm *i* and year *t*, *EDF* is default risk, *Co-option* as an independent variable, *Z* is a set of controls, which includes board size (*Ln Board Size*), board independent (*Independent*), the market value of equity (*Ln Equity*), the book value of debt

(*Ln Debt*), the reciprocal of the annualized standard deviation of stock return ($1/\sigma_E$), annual excess stock return (*Excess Return*), profitability (*ROA*), the proportion share ownership held by institutional blockholders (*Blockholder*), Amihud measure of illiquidity (*Amihud*), dividends to total assets ratio (*Dividends/Assets*), and the proportion of female directors serving on the board of directors (*Female*).

I will perform the regression on the ESG scores and separately on ESG Controversies instead of the Co-option, using the following fixed-effect regression with standard errors corrected for heterogeneity and using firm and/or year as fixed effects:

$$EDF_{it} = \alpha + \beta_1 ESG\_score_{it} + \beta_2 Z_{it} + \varepsilon_t + \gamma_i + \delta_t$$

where control variables are the market value of equity (lnEquity), the book value of Debt (lnDebt), the inverse volatility of stock return ($1/\sigma_E$), annual excess return (Excess return), return on assets as a profitability measure (ROA) and illiquidity measure (*Amihud*).

ESG score provided by Refinitiv is based on 500 company-level ESG measures, that are assessed on materiality (weights 1 to 10 given for each measure depending on the importance of the measure for a particular industry) and eventually grouped into 10 categories of three pillars – environmental, social and governance. Refinitiv uses percentile rank scoring methodology to calculate these 10 category scores:

$$score = \frac{no.of\ companies\ with\ a\ worse\ value + \frac{no.of\ companies\ with\ the\ same\ value\ included\ in\ the\ current\ one}{2}}{no.of\ companies\ with\ a\ value}$$

As Refinitiv (2021) states in their brochure, the score is designed to provide transparent and objective data, based on the company reported data and relative to peers. The scores are measured between 0 and 100, with 100 being the best score. The scores are updated regularly, usually once a year, but it can happen more often in case of a major event in a company. The scores are also not necessarily fixed once they are registered in the Refinitiv database, they are only "definitive" for the years prior to the past five years. This means that corrections can be added for the past five years' data points in case of the company's restatements or changes in the underlying data (Refinitiv, 2021). This can be potentially dangerous in terms of further analysis, where ESG-data is used, as pointed out by Berg et al. (2021).

For ESG Controversies score calculation, Refinitiv identifies 23 controversy topics and collects data from the global media (Refinitiv, 2021). Therefore, this data is not provided by the company but is independently collected based on the company's publicity regarding a scandal or any other controversial event. Some events may continue affecting the company's reputation in the following years. Also, Refinitiv states, that the controversies score addresses the market cap bias by using severity rates, as larger companies usually attract more attention. The ESG Controversies score is measured between 0 and 100, with 100 indicating that a company had no controversies.

3.3 Control variables

Baghdadi et al. (2019) control the five direct determinants of default risk: the natural logarithm of the market value of equity (*Ln Equity*), the natural logarithm of the face value of debt (*Ln Debt*), the inverse of annualized stock volatility ($1/\sigma_E$), the difference between the stock's annual return and the value-weighted return (*Excess Return*), and the ratio of net income to the total assets (*ROA*). They also control for stock liquidity referring to Brogaard et al.'s (2017) paper, which points to a strong relationship between the stock liquidity, and the firm's bankruptcy risk. Baghdadi et al. use for this purpose illiquidity measure (*Amihud*) suggested by Amihud (2002). *Amihud* measure is defined as the annual average of the daily ratio of the absolute value of stock return and Euro trading volume, multiplied by one million.

I use the same control variables as well, calculated the same way, and retrieving the initial value for calculations from the Refinitiv Screener and Refinitiv Datastream. Unlike Baghdadi et al., I do not control for corporate governance, the board size, the independent directors on the board, dividends to total assets ratio, and the proportion of female directors serving on the board of directors. All variables had been winsorized at the 1st and 99th percentiles to alleviate the effects of outliers. The one exception is default frequency as its values are naturally bounded between 0 and 1.

Table 1 below presents summary statistics for the chosen variables, while Table 2 contains the correlation results for the same variables.

Table 1. Summary statistics

This table presents descriptive statistics for the variables used in this study. The sample consists of 8460 firm-year observations during the 2000-2019 period, representing 423 non-financial European public companies. A detailed variable definition is provided in Appendix.

Variable	Mean	Std.dev.	P25	Median	P75
1. *Dependent variable*					
EDF	0,02	0,118	0,000	0,000	0,000
2. *Independent variables*					
ESG_score	53,30	20,854	37,03	54,69	69,10
ESG_contr	86,93	26,343	91,67	100	100
3. *Other variables*					
lnEquity	21,88	1,583	20,79	21,82	22,93
Excess return	0,16	1,954	-0,07	0,13	0,32
lnDebt	18,88	4,312	18,28	19,76	21,04
$1/\sigma_E$	4,45	2,243	2,97	4,11	5,53
ROA	0,06	0,068	0,03	0,05	0,08
Annual return	0,16	1,960	-0,07	0,14	0,33
Amihud	0,02	0,240	0,00006	0,0003	0,002

As can be seen from the summary table, the EDF measure lies between 0 and 1, where measures located closer to 0 indicate a lower probability of default. The mean EDF is 0,02 for the entire sample. From the correlation table, we see that EDF is negatively correlated with most of the variables and on a statistically significant level of 1 or 5% (except for the ESG Controversies score). The slightly positively correlated measures are lnDebt and Amihud (significant at 1% level).

The correlation between ESG score and EDF is negative (however, not statistically significant), which might suggest that their relationship is negative. But to make any more conclusive statements, further analysis should be conducted. The influence of control variables and unobserved variables needs to be addressed to establish the relationship between the probability of default and ESG activities.

Table 2. Correlation results

This table presents correlation results for the variables I used in the study. The sample consists of 8460 firm-year observations during the 2000-2019 period, representing 423 non-financial European public companies. A detailed variable definition is provided in Appendix. *,** and *** denote significance at the 10, 5, and 1% levels.

Variable	EDF	ESG_score	ESG_contr	lnEquity	Excess return	lnDebt	$1/\sigma_E$	ROA	Annual return
EDF	1,00								
ESG_score	-0,04**	1,00							
ESG_contr	-0,02	-0,3***	1,00						
lnEquity	-0,24***	0,55***	-0,34***	1,00					
Excess return	-0,07***	-0,04***	0,02*	0,03*	1,00				
lnDebt	0,05***	0,32***	-0,2***	0,38***	-0,02	1,00			
$1/\sigma_E$	-0,22***	0,17***	-0,02	0,36***	0,002	0,1***	1,00		
ROA	-0,13***	-0,06***	0,04***	0,14***	0,03**	-0,25***	0,12***	1,00	
Annual return	-0,08***	-0,04***	0,03*	0,03*	0,1***	-0,02	0,01	0,03*	1,00
Amihud	0,02***	-0,05***	0,02	-0,08***	0,004	-0,007	-0,05***	-0,02	0,004

ESG score and ESG Controversies score have a maximum value of 100, which indicates the best ESG performance. The mean for ESG score is 53,3 and for ESG Controversies score is 86,9. The correlation between these two measures is negative and significant at a 1% level. The correlation between ESG score and all other variables is significant at 1% level, it is mostly negative, except for *lnEquity*, *lnDebt,* and *Inverse volatility*. On the other hand, ESG Controversies is only significantly correlated with five variables: slightly positively at 10% significance level with Annual return and Excess return, at 1% significance level positively correlated with ROA, and at 1% significance level negatively correlated with lnEquity and lnDebt.

4. Results

In this section, I present the results of the regressions and discuss them. Following the Baghdadi et al. (2019), I also perform an OLS regression of the default risk EDF, however not on Co-option as the reference paper has done, but on the ESG scores:

$$EDF_{it} = \alpha + \beta_1 ESG\_score_{it} + \beta_2 Z_{it} + \varepsilon_t$$

Here, EDF_{it} is the default risk, ESG_score_{it} is the ESG score collected from the Thompson Reuters database, Z_{it} is the set of control variables and ε_t is the error term. The control variables are *lnEquity* the natural logarithm of Equity, *lnDebt* the natural logarithm of the face value of Debt (calculates as the short-term debt plus 0,5 of the long-term debt), $1/\sigma_E$ the inverse stock volatility, *ROA* the return on assets (calculated as the net income divided by the total assets) and *Excess_return* the excess return (calculated as the difference between the total return of the firm and the market return taken as the CRSP value-weighted return.

I first ran the OLS regression without including any control variables, then I ran further regressions while adding control variables one by one. And finally, I have performed fixed-effect regressions with all control variables included and using the combination of both the firm and/or the year as a fixed effect:

$$EDF_{it} = \alpha + \beta_1 ESG\_score_{it} + \beta_2 Z_{it} + \varepsilon_t + \gamma_i + \delta_t$$

4.1 Analysis of EDF

The measure of default risk lies between 0 and 1, with a higher measure indicating a higher probability of default. Figure 1 below presents mean EDF across the years for the sample of 423 European firms for 2000-2019. For most of the years, the average EDF stays well below the 0,05 mark, indicating an average low probability of default. There are clear spikes in the results in the years 2002, 2011, 2015, 2018, and especially in 2008, when it reaches its maximum in the timeframe in question 0,167. These are expected results, as years of economic distress have a clear effect on the firms' performance and ability to fulfill the debt obligations.

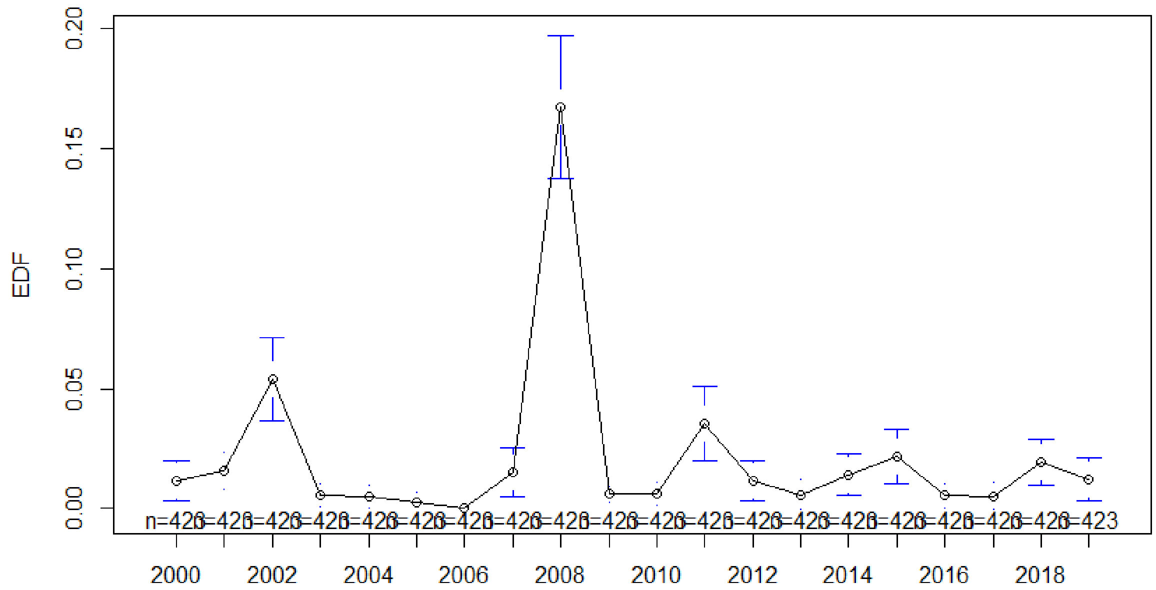

Figure 1. Mean EDF across the sample of 423 firms in the 2000-2019 timeframe

Figure 2 on the other hand, illustrates the distribution of the EDF for 423 firms in the sample during the time in question, about 8460 firm-year observations. The majority of firms have an average probability of default measure around zero-mark, which is in line with other authors’ results. Note, this illustration does not exclude years of economic distress.

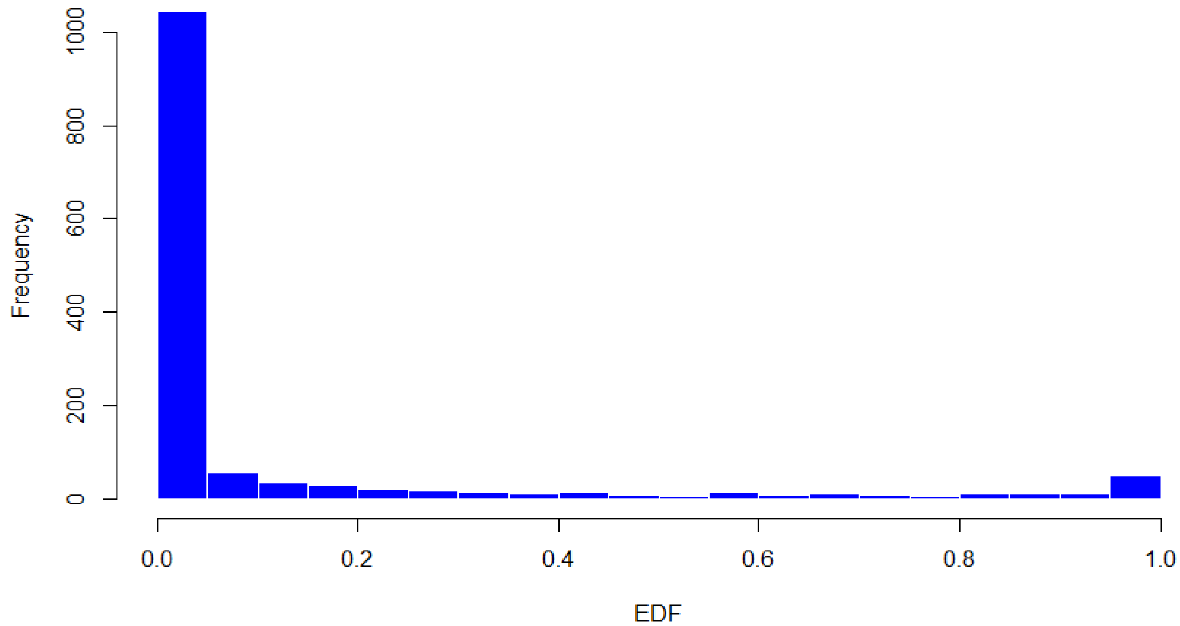

Figure 2. EDF distribution across 423 firms for 2000-2019

Analyzing the EDF results further, I have measured the average probability of default across a total of 23 industries presented in my data (see Figure 3 and Table 3 below). The top three industries with the highest average EDFs in the 2000-2019 period are Automobiles & Auto Parts, Retailers, and Energy – Fossil fuels. While they are at the top of the list, the values of EDF are considerably less than 1 – 0,0494; 0,0413 and 0,0406 respectively. The three industries having the lowest average EDFs are Pharmaceuticals & Medical Research, Consumer Goods Conglomerates, and Personal & Household Products & Services with values being significantly below the 0,01 mark.

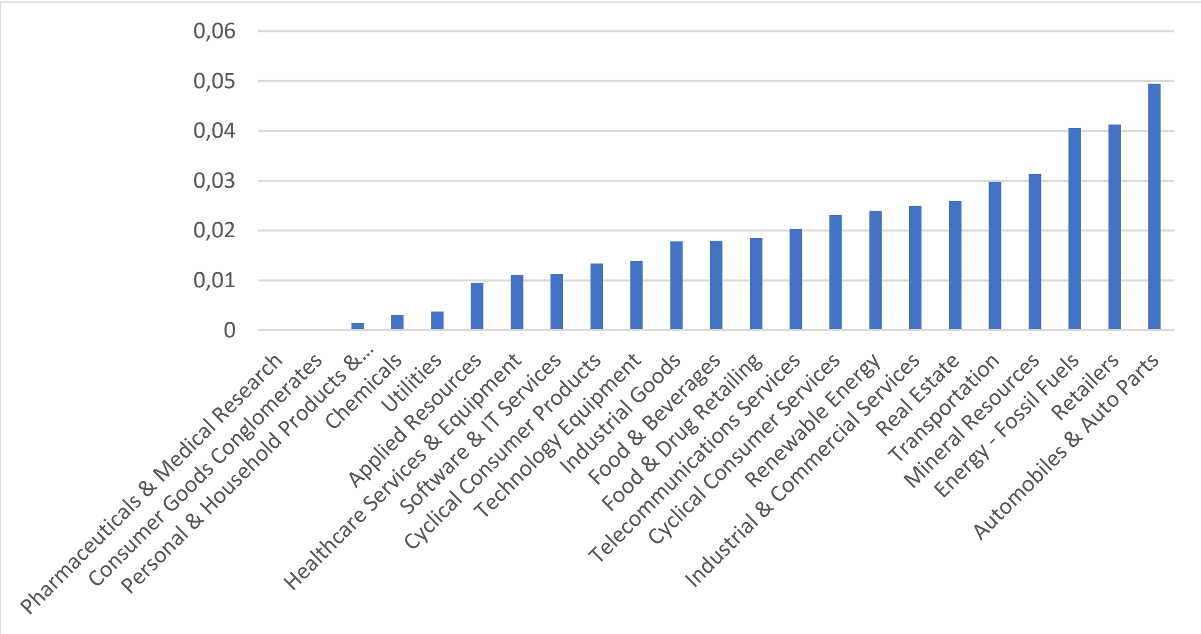

Figure 3. EDF distribution across the 23 industries presented in the sample.

Table 3. Average EDF across industries within the sample

TRBC Business Sector Name	N	%	Avg_EDF
Renewable Energy	1	0 %	0,023936
Consumer Goods Conglomerates	3	1 %	0,000191
Applied Resources	6	1 %	0,009503
Personal & Household Products & Services	7	2 %	0,001451
Food & Drug Retailing	10	2 %	0,018443
Automobiles & Auto Parts	13	3 %	0,049418
Healthcare Services & Equipment	13	3 %	0,011111
Software & IT Services	13	3 %	0,011252
Pharmaceuticals & Medical Research	15	4 %	0,000125
Technology Equipment	15	4 %	0,013915
Transportation	15	4 %	0,029806
Chemicals	16	4 %	0,00309
Retailers	16	4 %	0,041287
Telecommunications Services	18	4 %	0,020342
Utilities	18	4 %	0,003768
Food & Beverages	21	5 %	0,017928
Mineral Resources	25	6 %	0,031399
Energy - Fossil Fuels	27	6 %	0,040602
Real Estate	27	6 %	0,02595
Cyclical Consumer Products	28	7 %	0,013385
Cyclical Consumer Services	28	7 %	0,023102
Industrial Goods	40	10 %	0,01781
Industrial & Commercial Services	46	11 %	0,024985
Total/Average (std. deviation)	421	100 %	0,019 (0,014)

However, if I exclude the economic crisis year 2008, the results are slightly different (see Figure 4 below). The top three industries with the highest average EDFs are Energy – Fossil fuels, Renewable Energy, and Retailers. The bottom three industries (however less prone to distress) are still Pharmaceuticals & Medical Research and Consumer Goods Conglomerates, but also Applied Resources.

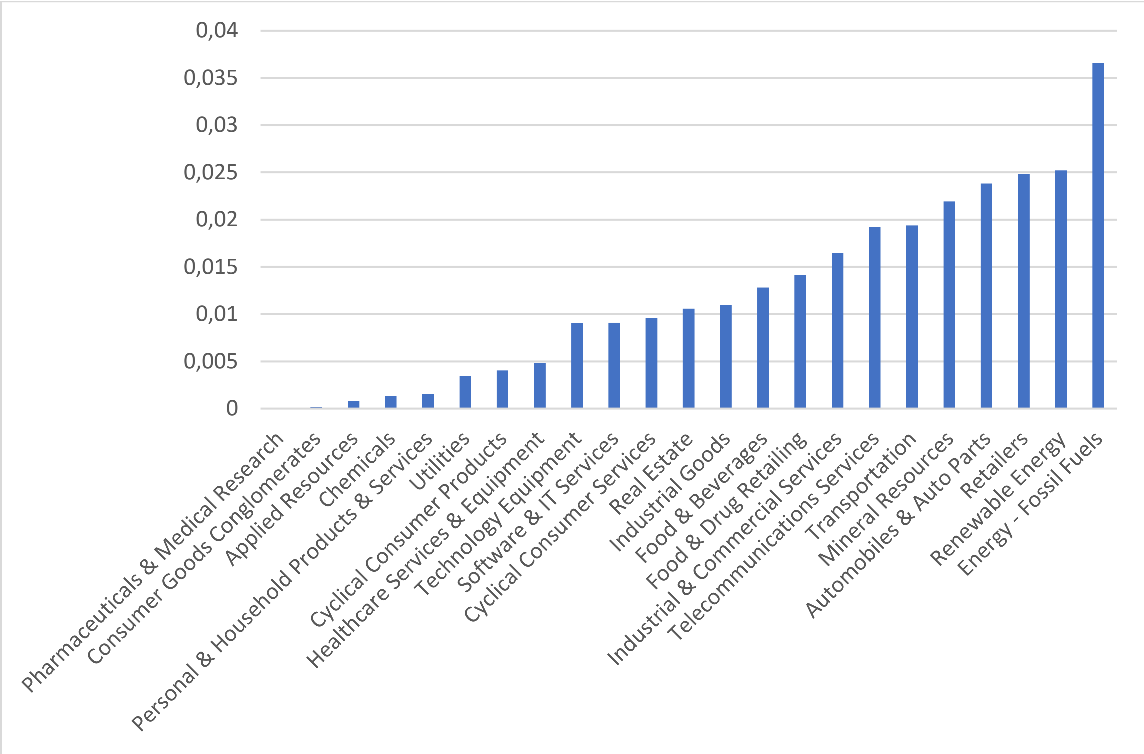

Figure 4. Distribution of EDF measures across industries, excluding the crisis year 2008

Further, I looked at the top three industries with the highest EDF over the period in dynamic. Note, in the previous graph 2008 has been removed, but the below Figure 5 includes 2008. Energy – fossil fuels industry has a highly volatile EDF trajectory with spikes in 2002, 2008, 2011, 2015, and 2017.

This is expected, because of the dependence on the oil prices and them being affected in every economic downturn. Renewable energy, on the other hand, does not seem to have been affected by the 2008 crisis like most other industries. The top three industries with the highest EDFs in 2008 were Automobiles & Auto parts, Retailers, and Real Estate (see Figure 6 below).

Renewable energy had a slightly higher probability of default is 2002 and later only one more spike in the entire 20-year time span, in 2012. The rest of the time, it is an industry with one of the lowest EDFs. Note, as shown further in this section of my thesis, this industry is only represented by one firm in my sample, and therefore it is hard to generalize the results off-sample.

Retailers' EDF reflects well the global economic downturns, having elevated EDF especially in 2008 and 2011.

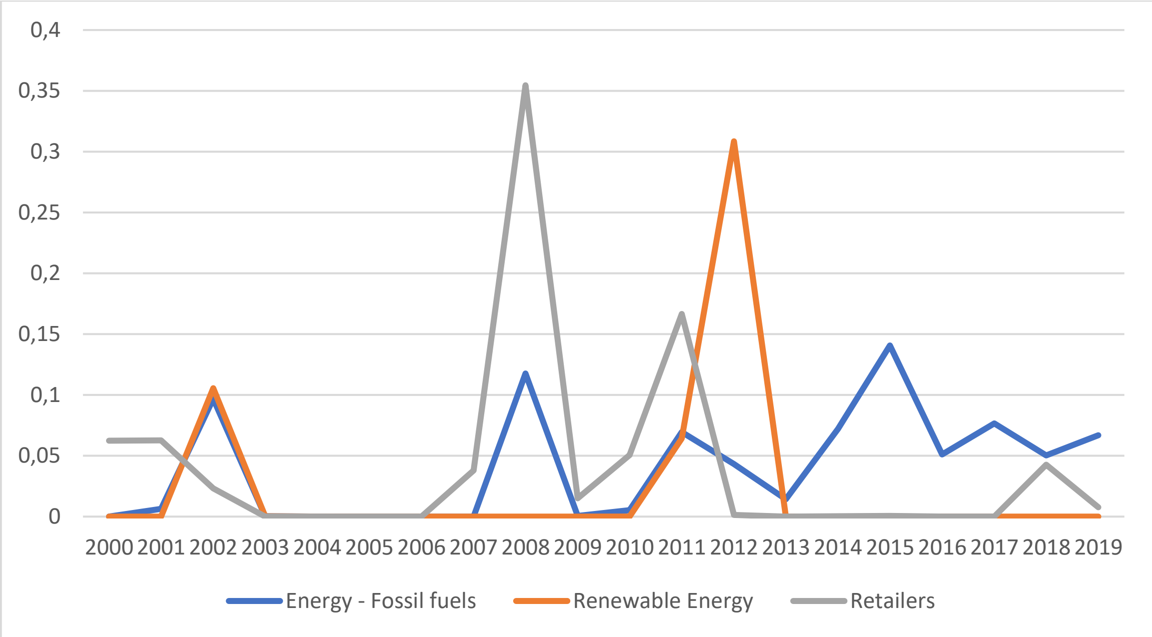

Figure 5. Top three industries with the highest average EDF measures across the 2000-2019 timeframe.

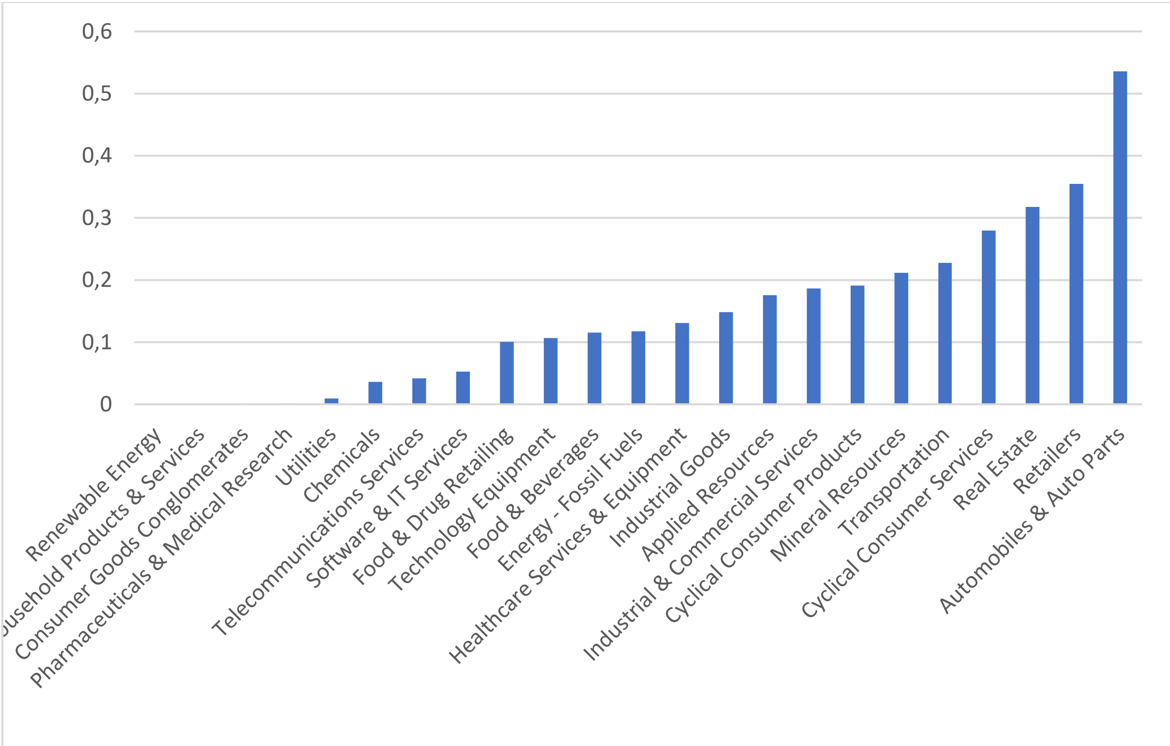

Figure 6. Average industry EDF in the crisis year 2008.

4.2 Analysis of ESG score and ESG Controversies

The summary table 3 below shows the shares of the sample's firms for each industry. Most of the firms in the sample are in the Industrial & Commercial Services and Industrial Goods, each account for 11% and 10% of the sample, respectively. Less than ten firms represent the following industries: Personal & Household Products & Services, Applied Resources, Consumer Goods Conglomerates, and Renewable Energy. Notable, the Renewable Energy industry is represented by only one firm in the sample.

Table 4. ESG Scores and ESG Controversies scores distribution across the sample

TRBC Business Sector Name	N	%	Avg_ESG_score	Avg_ESG_contr
Renewable Energy	1	0 %	61,36	88,16
Consumer Goods Conglomerates	3	1 %	54,59	75,21
Applied Resources	6	1 %	59,32	88,17
Personal & Household Products & Services	7	2 %	54,83	77,73
Food & Drug Retailing	10	2 %	60,64	82,21
Automobiles & Auto Parts	13	3 %	56,94	73,31
Healthcare Services & Equipment	13	3 %	51,45	87,80
Software & IT Services	13	3 %	48,62	94,82
Pharmaceuticals & Medical Research	15	4 %	57,66	72,66
Technology Equipment	15	4 %	51,73	91,29
Transportation	15	4 %	47,13	81,14
Chemicals	16	4 %	54,24	91,26
Retailers	16	4 %	49,96	93,48
Telecommunications Services	18	4 %	55,55	76,99
Utilities	18	4 %	64,14	85,11
Food & Beverages	21	5 %	55,44	85,97
Mineral Resources	25	6 %	58,08	78,83
Energy - Fossil Fuels	27	6 %	49,97	85,30
Real Estate	27	6 %	54,49	98,83
Cyclical Consumer Products	28	7 %	50,17	93,41
Cyclical Consumer Services	28	7 %	52,86	89,90
Industrial Goods	40	10 %	50,45	86,60
Industrial & Commercial Services	46	11 %	50,24	91,37
Total/Average (std. deviation)	421	100 %	54,34 (4,44)	85,63 (7,26)

The overall distribution of the ESG scores across the sample for the years 2001-2019 is shown on the graph below:

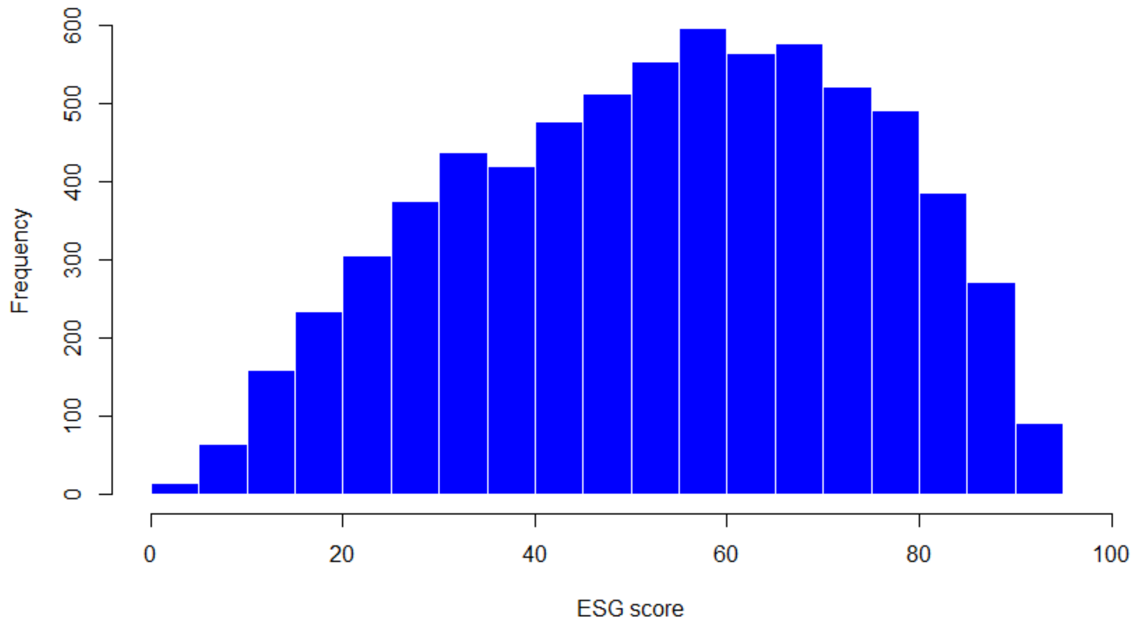

Figure 7. ESG score distribution across the 423 non-financial European public firms in 2001-2019

I further investigate ESG scores' distribution across the time 2001-2019 (there were no registered ESG activities for the firms in the sample in 2000 reported by Refinitiv), which is illustrated in Figure 8 below. The number of the firms reporting the ESG data has grown over time, only by 2010 did all 423 firms start reporting the data needed for assigning the ESG score. There is an upward trend in the average ESG scores over time, also after 2010 when all firms are included in the sample. This was expected as the sustainability trend has started and been developing over the last decade, more regulations have been passed over the years as well as the firms try to use ESG activities as a competitive advantage.

ESG controversies scores' distribution across the sample is presented in Figure 9 below. As can be noticed, most firms tend to have higher ESG Controversies scores, located close to 100-mark, which indicates the absence of the scandals in the ESG performance. This measure is composed based on the independent reports of the controversial activities in the media as opposed to the ESG score, which is based on the data reported by the firms

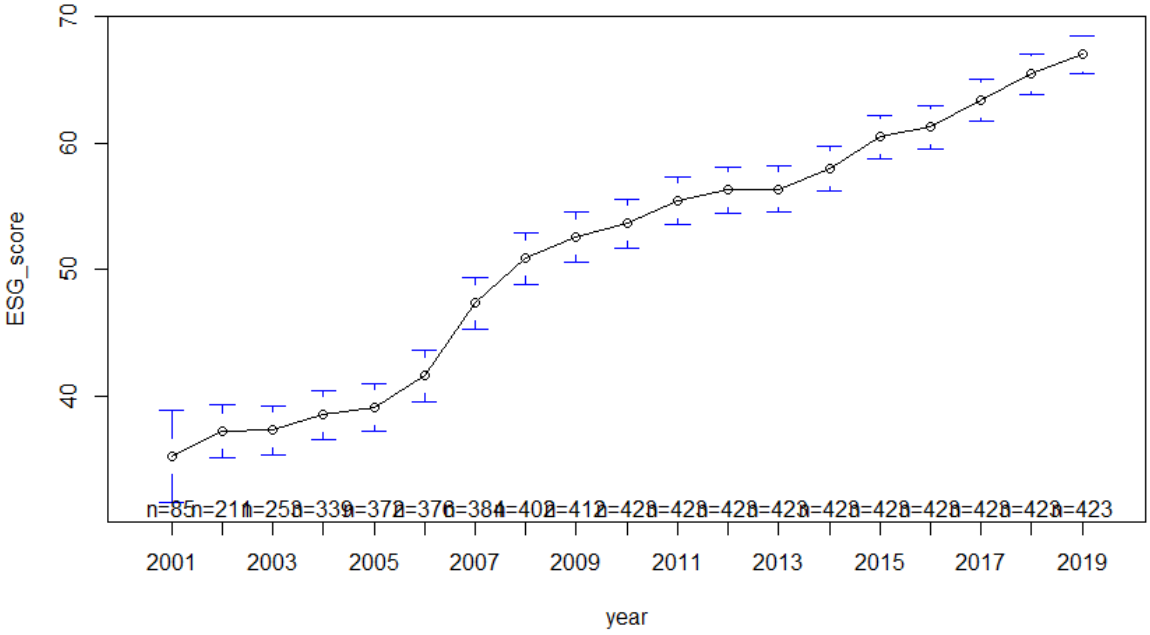

Figure 8. Average ESG score across the time span of 2001-2019 for the sample of 423 European non-financial public firms.

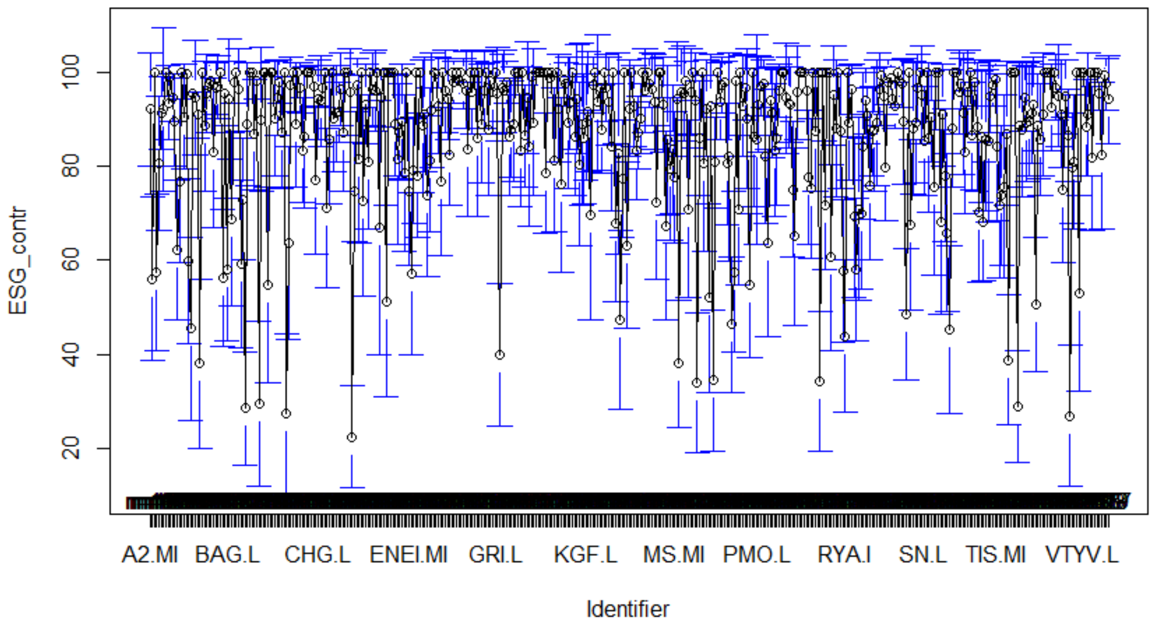

Figure 9. Distribution of average ESG Controversies scores for each company in the sample.

The distribution of the ESG Controversies score across time has been fluctuating between 85 and 90 in 2001-2013 (also note the growing number of firms), which is presented in Figure 10 below. Since 2010, it has been mostly improving and reached its peak in 2015. However, after that, the average ESG Controversies scores across the sample have been decreasing and fell below the 85-mark in 2019, This shows how different the ESG score and ESG Controversy scores are. The former is based on the actual measures provided by the firms, while the latter is based on the controversial events happening to the firms in the sample.

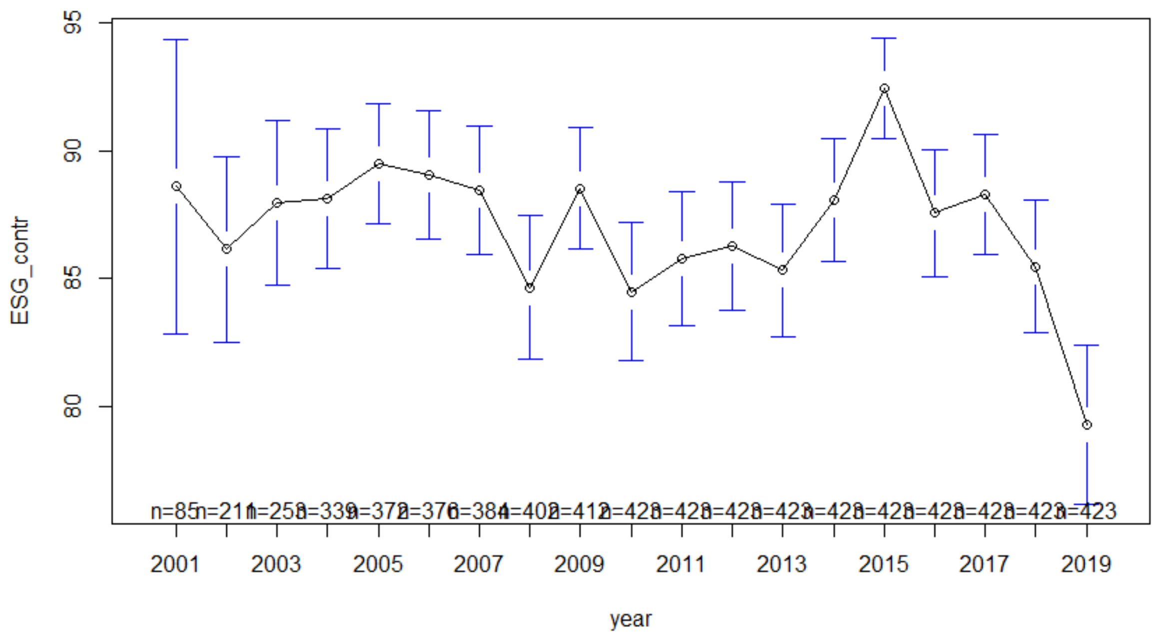

Figure 10. Distribution of ESG Controversies score over the time of 2001-2019

ESG scores and ESG Controversies scores distributions across industries are presented in Figure 11 below. There is no significant spread between the ESG scores among the industries in the sample, they are mostly between 40 and 60 on average. There is, however,

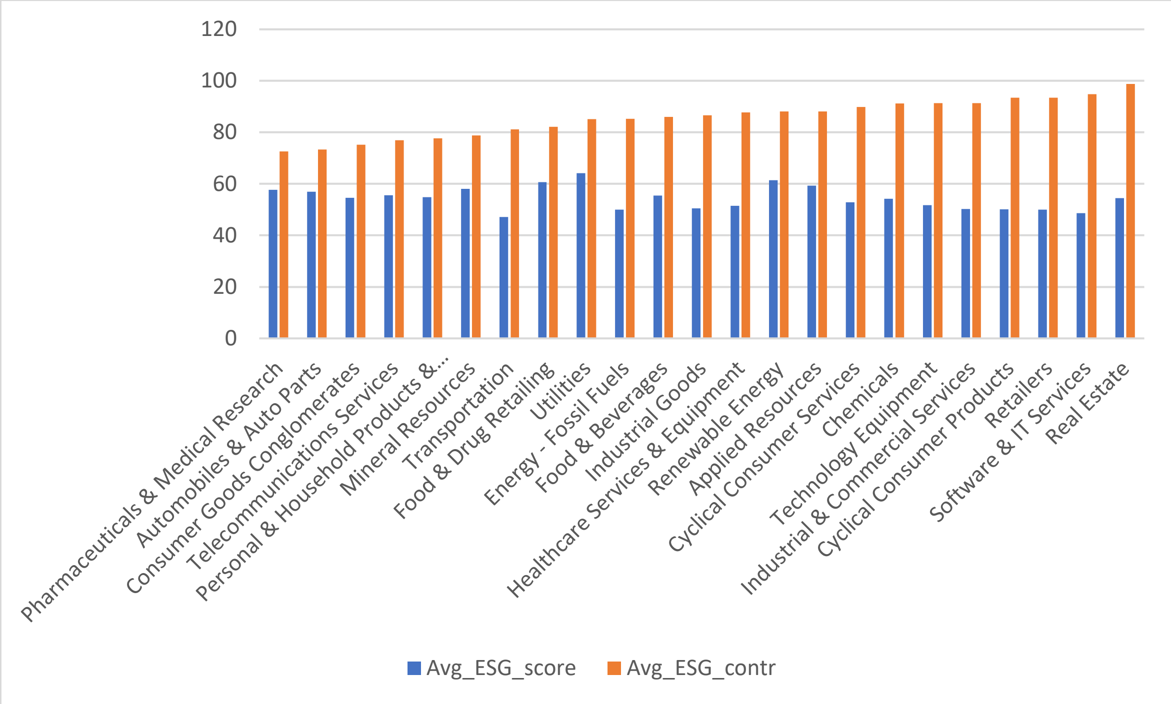

Figure 11. Distribution of ESG Scores and ESG Controversies scores across industries in the sample

a clear trend in the ESG controversies scores with the Retailers, Software & IT Services, and Real Estate being the top three industries with the highest scores. A higher score indicates less controversial events in the industry. However, although the top three industries have the highest ESG controversies scores, their ESG scores are not the highest in the sample (the three industries with the top ESG scores are Utilities, Renewable Energy, and Food & Drug Retailing).

In their working paper on the sample of the U.S. and European firms between 2003 and 2017, Bannier et al. (2019) analyze ESG data of over 10000 firm-year observations in the U.S. and over 11000 firm-year observations in Europe. They have included financial firms in the sample as well. They found that the total ESG score for the U.S. firms in their sample was 50,8 (standard deviation 16,76) and for the European firms slightly higher 56,7 (standard deviation 16,26). In my sample the result is somewhat similar, the total ESG score is 53,28 with a standard deviation of 20,84. Below is summary table 4 with the entire sample average ESG scores and ESG Controversies scores.

Table 5. Average ESG Scores and ESG Controversies scores for the sample

Score	Mean	STD
ESG Score	53,28	20,84
ESG Controversies Score	87,03	26,25

Dorfleitner et al. (2020), focusing on the ESG Controversies score and profitability of ESG-focused portfolios, study both European and U.S. firms between 2002-2018. Their sample includes approximately 900 European firms and 1000 U.S. firms (number varies between the years), including Financial industry firms, but excluding penny stocks. Their findings show a negative correlation between the ESG score, and the Controversies score for the entire sample – (-0,3107) explaining further that companies with higher ESG scores tend to have lower Controversies score, possibly because they are under a closer watch – "the higher you fly, the harder you fall". In my sample, I did not find similar results, the correlation between the ESG scores and Controversies score in my case is positive – (0,4568), though they do not fully correlate. Possibly, in the European sample, the situation could be different, if the companies reporting their ESG scores are also trying to be careful with any possible negative publicity related to the ESG. As for the average Controversies scores for the U.S. and European firms, Dorfleitner et al. report average ESG Controversies scores of 46,53 (21,91) and 48,36 (21,24) respectively (standard deviation is stated in brackets). In my sample, the average ESG Controversies score for the European firms is 87,03 (26,25).

4.2 Regression results

The first panel of regression results is reported in Table 6 below. I started with OLS regression on EDF and ESG_score including control variables one by one. The Model 1 regression shows the statistically significant at 5%-level negative result indicating that the ESG activities decrease the probability of default. With one standard deviation increase in the ESG score, the EDF decreases by 0,000205. It represents a 20,4% decrease compared to the EDF sample mean[1]. This result would suggest no support for my first hypothesis, however, with the addition of the first and the following control variables, we can notice

[1] The economic significance is computed based on the coefficient on ESG_score (0,000205) multiplied by the standard deviation on the ESG_score variable from Table 1 (20,854), which equals 0,004275. The effect represents roughly 20,4% of the sample mean of EDF from Table 1 (0,02).

that the sign of the ESG_score coefficient changes to positive, indicating the positive relation between the ESG_score and probability of default (Model 2-7, all ESG_score coefficients are statistically significant at 1%-level). As mentioned in the theoretical overview, the causality could go in the opposite direction as well.

Table 6. OLS regression of EDF and ESG_score

	Dependant variable: EDF						
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ESG_score	-0,000205**	0,000796***	0,000766***	0,000627***	0,000595***	0,000602***	0,000605***
	(-2.6739)	(7,2870)	(6,2811)	(5,5658)	(5,4872)	(5,5148)	(5,5477)
lnEquity		-0,002512***	-0,02476***	-0,02811***	-0,02437***	-0,02281***	-0,022648***
		(-10.346)	(-9,4638)	(-10,0705)	(-9,2881)	(-8,8371)	(-8,8174)
Excess_return			-0,008002	-0,007643	-0,007816	-0,007059	-0,007079
			(-0,4461)	(-0,4366)	(-0,4502)	(-0,4205)	(-0,4210)
lnDebt				0,004198***	0,004079***	0,00362***	0,003598***
				(8,7153)	-8,9224	(7,9890)	(7,9542)
1/σE					-0,006983***	-0,00784***	-0,007794***
					(-7,8485)	(-10,1828)	(-10,1506)
ROA						-0,005452	-0,054444
						(-1,8490)	(-1,8401)
Amihud							0,059252**
							(2,7382)
Firm Fixed effect	NO	NO	NO	NO	NO	NO	NO
Year Fixed effect	NO	NO	NO	NO	NO	NO	NO
Observations	7064	7064	7064	7064	7064	6929	6929
Adjusted R^2	0,00114	0,07391	0,07791	0,09678	0,1121	0,1127	0,1136
F-statistic	9 058	282,9	199,9	190,2	179,4	147,7	127,8

This table reports on the estimates of the OLS regression with the dependant variable being the probability of default EDF and the independent variable ESG-score. Models 1-7 differ by the inclusion of control variables. No fixed effects have been applied. The regressions are performed on an unbalanced sample, with the total number of firm-year observations varying between 6929 and 7064, representing 423 European non-financial public firms between the years 2000-2019. Standard errors have been controlled for robustness. T-values are reported in parentheses. ***, ** and * indicate a significance level of 1%, 5% and 10%.

By introducing the first control variable, the effect of the ESG_score becomes non-negative, which means that the increase in ESG_score by one unit increases the probability of default by 0,000796 or an 82% increase compared to the EDF sample mean. *lnEquity* thus has taken all the negative effects on EDF (-0,002512 at the 1% significance level). Another control variable contributing to the decrease of the probability of default (at a statistically significant level of 1%) is *Inverse volatility.* The statistical significance disappears for Excess_return and ROA after the robustness check.

The ESG_score coefficient slightly decreases after controlling for lnDebt in Model 4 and Model 5 and stays at around 0,0006 after all control variables have been added. It represents a 63% increase compared to the EDF sample mean.

The next step of the analysis is the relation between ESG_contr (ESG Controversies) and EDF. I run an OLS regression in the same manner as I did with the ESG_score variable, adding gradually control variables. The results are presented in Table 7 below. This result is interesting compared to the effect we observed from the ESG_score regression, as it shows the opposite effect of ESG_contr on EDF. ESG_contr has a negative relation to EDF in all models of my OLS_regression (Model 1-7), and the coefficients are statistically significant at 1%-level after adding already the first control variable.

Table 7. OLS- regression of EDF and ESG_contr

	Dependent variable: EDF						
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ESG_contr	-0,000066	-0,000429***	-0,000482***	-0,000427***	-0,000366***	-0,000362***	-0,000362***
	(-1,0114)	(-6,5534)	(-5,9332)	(-5,5762)	(9,8016)	(-4,784)	(-4,7805)
lnEquity		-0,002205***	-0,021846***	-0,02611***	-0,022403***	-0,02076***	-0,020583***
		(-10.3856)	(-9,7503)	(-10,4332)	(-9,4460)	(-8,9485)	(-8,9177)
Excess_return			-0,008539	-0,00803	-0,008209	-0,00744	-0,007465
			(-0,4706)	(-0,4555)	(-0,4690)	(-0,4396)	(-0,4402)
lnDebt				0,004392***	0,004288***	0,00378***	0,003768***
				(8,7858)	(8,9476)	(7,9825)	(7,9536)
1/σE					-0,006714***	-0,00743***	-0,007383***
					(-8,0360)	(-9,9351)	(-9,9042)
ROA						-0,064084*	-0,064102*
						(-2,0799)	(-2,0734)
Amihud							0,056838**
							(2,7266)
Firm Fixed effect	NO	NO	NO	NO	NO	NO	NO
Year Fixed effect	NO	NO	NO	NO	NO	NO	NO
Observations	7064	7064	7064	7064	7064	6929	6929
Adjusted R^2	0,000068	0,0708	0,077991	0,09638	0,1121	0,1108	0,1116
F-statistic	1,48	270,1	199,9	189,3	179,4	144,9	125,3

This table reports on the estimates of the OLS regression with the dependant variable being the probability of default EDF and the independent variable ESG_contr. Models 1-7 differ by the inclusion of control variables. No fixed effects have been applied. The regressions are performed on an unbalanced sample, with the total number of firm-year observations varying between 6929 and 7064, representing 423 European non-financial public firms between the years 2000-2019. Standard errors have been controlled for robustness. T-values are reported in parentheses. ***, ** and * indicate a significance level of 1%, 5% and 10%.

After all control variables have been added, EDF is decreased by 0,000362 units with an increase in one unit of ESG_contr. This represents a 47,7% decrease compared to the EDF sample mean. This result supports my third hypothesis since the higher the ESG-controversy score is the better the firm handles its ESG risks.

We can see the negative effect is slightly being taken away by adding lnEquity, lnDebt, Inverse volatility, and ROA variables. lnEquity, Inverse volatility, and ROA have a negative effect on EDF as well (lnEquity and Inverse volatility at 1% significance level and ROA at 10% significance level). lnDebt and Amihud positively affect EDF at 1% and 5% significance level respectively.

Table 8. Fixed-effect regression on EDF and ESG_score, year- and firm-fixed

	Dependent variable: EDF						
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ESG_score	-0,000077	0,000336*	0,000335*	0,000321*	0,000321*	0,000341*	0,000342*
	(-0,5601)	(2,3346)	(2,3326)	(2,2635)	(2,2655)	(2,4432)	(2,4529)
lnEquity		-0,067334***	-0,067304***	-0,067257***	-0,06645***	-0,065556***	-0,065401***
		(-12,9998)	(-12,4411)	(-12,5030)	(-12,3051)	(-11,9823)	(-11,9478)
Excess_return			-0,000154	-0,000145	-0,000265	-0,000117	-0,000133
			(-0,0138)	(-0,0131)	(-0,0237)	(-0,0108)	(-0,0122)
lnDebt				0,002025***	0,002006***	0,001771***	0,001771***
				(4,5737)	(4,5333)	(3,9401)	(3,9376)
1/σE					-0,001285*	-0,001106	-0,001089
					(-2,2169)	(-1,8383)	(-1,8123)
ROA						-0,046886*	-0,047227
						(-1,3708)	(-1,3785)
Amihud							0,019925
							(1,0411)
Firm Fixed effect	YES	YES	YES	YES	YES	YES	YES
Year Fixed effect	YES	YES	YES	YES	YES	YES	YES
Observations	7064	7064	7064	7064	7064	6929	6929
Adjusted R^2	0,209	0,2455	0,2454	0,247	0,2473	0,2452	0,2452
F-statistic	3,966	6,199	6,184	6,219	6,214	6,057	6,046

This table reports on the estimates of the fixed-effect regression with the dependant variable being the probability of default EDF and the independent variable ESG_score Models 1-7 differ by the inclusion of control variables. Fixed effects on year and firm have been applied. The regressions are performed on an unbalanced sample, with the total number of firm-year observations varying between 6929 and 7064, representing 423 European non-financial public firms between the years 2000-2019. Standard errors have been controlled for robustness. T-values are reported in parentheses. ***, ** and * indicate a significance level of 1%, 5% and 10%.

Further, I continue my analysis by running fixed-effect regressions. I fix for both year and firm first, then for a year only, and then for firm only. Tables 8-10 report results of fixed-effect regressions on EDF and ESG_score, Tables 11-13 report results of fixed-effect regressions on EDF and ESG_contr.

After adding the fixed effect of the year and the firm (Table 8 above), the ESG_score's coefficients are considerably smaller and only significant at 10%-level in Models 2-7. Similar to the linear regression results, the fixed-effect regression results show that ESG_score affects the default probability positively after adding control variables as well. The statistical significance of the ESG_score coefficients is considerably lower in the first fixed-effect regression when both firm and year effects have been fixed. While fixing for both time and firm effects, the ESG_score coefficient in the last model 7 (Table 8) is 0,000342, though at the significance level of only 10%. It represents a 35,7% increase in EDF in terms of economical significance when compared to the EDF sample mean. In this case, when both firm and time effects are fixed, it is hard to determine what takes away the ESG_score effect. Therefore, I continue with the fixed-effect regressions – fixing for the firm and for time separately.

The results of these two regressions are presented in table 9 (fixed year effect) and 10 (fixed firm effect). We can see that the coefficient of ESG_score after all control variables have been introduced is smaller when the year effect has been fixed. The coefficients in both regressions are statistically significant at 1%-level. Both regressions however support my first hypothesis – ESG_score is positively related to the probability of default. When the year-effect is fixed, ESG_score has a positive coefficient of 0,000633 (66% increase compared to the EDF sample mean), and when the firm-effect is fixed, ESG_score coefficient is positive 0,000866 (90,3% increase compared to the EDF sample mean). There is also a consistent and statistically significant at 1%-level positive relation of lnDebt and EDF in all three fixed-effect regressions, which is expected as Debt is one of the main determinants of the default risk. Interestingly, in the year-fixed effect regression, Amihud has a significant 5%-level positive effect on EDF, showing that with every 1-unit increase in Amihud, EDF increases by 0,06788. No significant effect has been shown in other fixed-effect regressions.

Table 9. Fixed-effect regression on EDF and ESG_score with fixed year effect

	Dependent variable: EDF						
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ESG_score	-0,000212*	0,000851***	0,000847***	0,000661***	0,000642***	0,000629***	0,000633***
	(-2,3502)	(7,0625)	(6,7402)	(5,6750)	(5,6393)	(-5,5229)	(5,5569)
lnEquity		-0,023158***	-0,023105***	-0,025822***	-0,023625***	-0,021672***	-0,021473***
		(-9,8368)	(-9,5512)	(-10,1183)	(-9,6583)	(-8,9580)	(-8,9482)
Excess_return			-0,001967	-0,001767	-0,002157	-0,001629	-0,001646
			(-0,1449)	(-0,1331)	(-0,1613)	(-0,1258)	(-0,1269)
lnDebt				0,003708***	0,003686***	0,003059***	0,00303***
				(8,6138)	(8,7812)	(7,1026)	(7,0741)
1/σE					-0,004628***	-0,005214***	-0,005151***
					(-6,1842)	(-7,3935)	(-7,3666)
ROA						-0,09002*	-0,090181*
						(-2,3881)	(-2,3833)
Amihud							0,06788**
							(2,8697)
Firm Fixed effect	NO	NO	NO	NO	NO	NO	NO
Year Fixed effect	YES	YES	YES	YES	YES	YES	YES
Observations	7064	7064	7064	7064	7064	6929	6929
Adjusted R^2	0,0964	0,1541	0,1542	0,1685	0,1744	0,1739	0,1751
F-statistic	40,65	64,34	62,33	66,07	65,88	61,78	59,83

This table reports on the estimates of the fixed-effect regression with the dependant variable being the probability of default EDF and the independent variable ESG_score Models 1-7 differ by the inclusion of control variables. Fixed effects on year have been applied. The regressions are performed on an unbalanced sample, with the total number of firm-year observations varying between 6929 and 7064, representing 423 European non-financial public firms between the years 2000-2019. Standard errors have been controlled for robustness. T-values are reported in parentheses. ***, ** and * indicate a significance level of 1%, 5% and 10%.

Table 10. Fixed-effect regression on EDF and ESG_score with firm-fixed effect

	Dependent variable: EDF						
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ESG_score	-0,000125	0,000946***	0,000911***	0,00089***	0,000871***	0,000886***	0,000886***
	(-1,3296)	(8,017)	(6,8412)	(6,7211)	(6,5878)	(6,5022)	(6,5029)
lnEquity		-0,073553***	-0,072329***	-0,072208***	-0,068835***	-0,068505***	-0,068423***
		(-14,240)	(-12,8911)	(-12,9152)	(-12,2991)	(-11,6917)	(-11,6583)
Excess_return			-0,005134	-0,005079	-0,005277	-0,004945	-0,004956
			(-0,3472)	(-0,3447)	(-0,3589)	(-0,3495)	(-0,3500)
lnDebt				0,002317***	0,002235***	0,002073***	0,002074***
				(4,8537)	(4,7324)	(4,3679)	(4,3676)
1/σE					-0,003579***	-0,003705***	-0,003698***
					(-5,4743)	(-5,8085)	(-5,7988)
ROA						-0,004032	-0,004168
						(-0,1069)	(-0,1105)
Amihud							0,013333
							(0,5685)
Firm Fixed effect	YES	YES	YES	YES	YES	YES	YES
Year Fixed effect	NO	NO	NO	NO	NO	NO	NO
Observations	7064	7064	7064	7064	7064	6929	6929
Adjusted R^2	0,0539	0,1848	0,1864	0,1887	0,1915	0,1907	0,1906
F-statistic	1,951	4,777	4,808	4,855	4,919	4,823	4,812

This table reports on the estimates of the fixed-effect regression with the dependant variable being the probability of default EDF and the independent variable ESG_score Models 1-7 differ by the inclusion of control variables. Fixed effects on the firm have been applied. The regressions are performed on an unbalanced sample, with the total number of firm-year observations varying between 6929 and 7064, representing 423 European non-financial public firms between the years 2000-2019. Standard errors have been controlled for robustness. T-values are reported in parentheses. ***, ** and * indicate a significance level of 1%, 5% and 10%.

The last part of the regression results analysis is the analysis of the fixed-effect regressions on EDF and ESG_contr. The results are presented in tables 11-13 below. When running a regression on EDF with ESG_contr and controlling for all control variables as well as using the year- and ticker-fixed effect, the regression does not produce significant results for the ESG_contr effects. Control variables lnEquity and lnDebt still have a statistically significant negative and positive relation with EDF respectively.

Table 11. Fixed-effect regression on EDF and ESG_Contr with fixing on year and firm

	Dependent variable: EDF						
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ESG_contr	-0,000079	0,000009	0,00001	0,000013	0,000015	-0,000011	-0,000012
	(-1,2056)	(0,1521)	(0,1527)	(0,2165)	(0,2330)	(-0,1878)	(-0,1943)
lnEquity		-0,066746***	-0,06697***	-0,066685***	-0,065879***	-0,064852***	-0,064697***
		(-13,3435)	(-12,5401)	(-12,5994)	(-12,3883)	(-11,9175)	(-11,8876)
Excess_return			-0,000261	-0,000249	-0,000368	-0,000217	-0,000233
			(-0,0233)	(-0,0223)	(-0,0328)	(-0,0201)	(-0,0215)
lnDebt				0,002057***	0,002038***	0,001796***	0,001795***
				(4,7094)	(4,6650)	(3,9784)	(3,9762)
1/σE					-0,001286*	-0,001103	-0,001086
					(-2,2645)	(-1,8427)	(-1,8159)
ROA						-0,049771	-0,050113
						(-1,4049)	(-1,4124)
Amihud							0,019466
							(1,0012)
Firm Fixed effect	YES	YES	YES	YES	YES	YES	YES
Year Fixed effect	YES	YES	YES	YES	YES	YES	YES
Observations	7064	7064	7064	7064	7064	6929	6929
Adjusted R^2	0,1564	0,2448	0,2447	0,2465	0,2467	0,2445	0,2445
F-statistic	3,97	6,18	6,166	6,203	6,197	6,039	6,027

This table reports on the estimates of the fixed-effect regression with the dependant variable being the probability of default EDF and the independent variable ESG_contr. Models 1-7 differ by the inclusion of control variables. Fixed effects on both firm and year have been applied. The regressions are performed on an unbalanced sample, with the total number of firm-year observations varying between 6929 and 7064, representing 423 European non-financial public firms between the years 2000-2019. Standard errors have been controlled for robustness. T-values are reported in parentheses. ***, ** and * indicate a significance level of 1%, 5% and 10%

When fixing for the year effect only, the ESG_contr coefficients become significant at 1%-level (Table 12, Model 2-7). In contrast to the ESG_score, the ESG_contr has a negative effect on EDF – (-0,000322) in Model 7, when all control variables have been introduced. It also represents a 42,4% decrease in EDF in relation to its sample mean. This result supports my third hypothesis – ESG Controversies is negatively related to the probability of default. It is also a good example of how ESG Score and ESG Controversies score do not affect in the same way.

Table 12. Fixed-effect regression on EDF and ESG_contr with fixing the year effect

	Dependent variable: EDF						
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ESG_contr	-0,000033	-0,000419***	-0,000417***	-0,000367***	-0,000333***	-0,000323***	-0,000322***
	(-0,5129)	(-5,6610)	(-5,4275)	(-5,0132)	(-4,6039)	(-4,4031)	(-4,3909)
lnEquity		-0,019654***	-0,01962***	-0,023711***	-0,021555***	-0,019624***	-0,019406***
		(-9,7148)	(-9,5207)	(-10,3586)	(-9,7849)	(-8,9777)	(-8,9614)
Excess_return			-0,002249	-0,00193	-0,00231	-0,001759	-0,001777
			(-0,1641)	(-0,1449)	(-0,1719)	(-0,1533)	(-0,1365)
lnDebt				0,004036***	0,004018***	0,003344***	0,003318***
				(9,2662)	(9,4278)	(7,6695)	(7,6384)
1/σE					-0,004372***	-0,004793***	-0,004734***
					(-6,5518)	(-7,2475)	(-7,2079)
ROA						-0,097813*	-0,098068*
						(-2,5505)	(-2,5470)
Amihud							0,06556**
							(2,8052)
Firm Fixed effect	NO	NO	NO	NO	NO	NO	NO
Year Fixed effect	YES	YES	YES	YES	YES	YES	YES
Observations	7064	7064	7064	7064	7064	6929	6929
Adjusted R^2	0,0953	0,1496	0,1498	0,1673	0,1725	0,1721	0,1732
F-statistic	40,18	63,12	60,25	65,51	65,03	61,02	59,06

This table reports on the estimates of the fixed-effect regression with the dependant variable being the probability of default EDF and the independent variable ESG_contr. Models 1-7 differ by the inclusion of control variables. Fixed effects on year have been applied. The regressions are performed on an unbalanced sample, with the total number of firm-year observations varying between 6929 and 7064, representing 423 European non-financial public firms between the years 2000-2019. Standard errors have been controlled for robustness. T-values are reported in parentheses. ***, ** and * indicate a significance level of 1%, 5% and 10%

On the other hand, when fixing the firm-effect, the regression does not produce significant results on the main independent variable ESG_contr (Table 13, Models 1-7).

Table 13. Fixed-effect regression on EDF and ESG_contr with fixing the firm-effect

	Dependent variable: EDF						
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ESG_contr	-0,000124	-0,000068	-0,000063	-0,000059	-0,000056	-0,000084	-0,000084
	(-1,873)	(-1,0901)	(-1,0183)	(-0,9557)	(-0,9078)	(-1,3925)	(-1,3983)
lnEquity		-0,066607***	-0,065427***	-0,065469***	-0,062037***	-0,061158***	-0,061075***
		(-14,5238)	(-12,6994)	(-12,7689)	(-12,1999)	(-11,9028)	(-11,8731)
Excess_return			-0,006286	-0,006198	-0,006384	-0,006041	-0,006053
			(-0,4086)	(-0,4051)	(-0,4189)	(-0,4117)	(-0,4121)
lnDebt				0,002527***	0,002435***	0,002233***	0,002335***
				(5,4437)	(5,2689)	(4,7515)	(4,7520)
1/σE					-0,003803***	-0,003986***	-0,003979***
					(-6,2680)	(-6,4669)	(-6,4467)
ROA						-0,023487	-0,023622
						(-0,6111)	(-0,6141)
Amihud							0,013459
							(0,5619)
Firm Fixed effect	YES	YES	YES	YES	YES	YES	YES
Year Fixed effect	NO	NO	NO	NO	NO	NO	NO
Observations	7064	7064	7064	7064	7064	6929	6929
Adjusted R^2	0,0542	0,1742	0,1766	0,1793	0,1826	0,1815	0,1814
F-statistic	1,96	4,513	4,564	4,622	4,694	4,598	4,588

This table reports on the estimates of the fixed-effect regression with the dependant variable being the probability of default EDF and the independent variable ESG_contr. Models 1-7 differ by the inclusion of control variables. Fixed effects on the firm have been applied. The regressions are performed on an unbalanced sample, with the total number of firm-year observations varying between 6929 and 7064, representing 423 European non-financial public firms between the years 2000-2019. Standard errors have been controlled for robustness. T-values are reported in parentheses. ***, ** and * indicate a significance level of 1%, 5% and 10%

5. Conclusion

This research is focusing on the effect of ESG activities of non-financial European public firms on the probability of default. I perform the study on data associated with ESG scores and ESG Controversies scores of 423 firms, about 8460 fir-year observations, available in the Refinitiv database in the investigation period of 2000-2019. For calculating the probability of default measure, I use the structural form of Merton's distance-to-default method, as described by Baghdadi et al. (2020).

Engagement in ESG activities may create a conflict of interest between management and stakeholders and agency problems occur. As pointed out by Barnea and Rubin (2010), management may enjoy benefits from higher ESG activities, while ignoring the value-optimization objectives. Cash outflow requirements for the ESG activities can lead to opportunity costs and potentially limit the access to the cash needed for the firm's value-optimization. This can in turn limit the firm's ability to pay its debt obligations and increase the default risk of the firm.

On the other hand, the ESG Controversies scores indicate the presence or absence of controversial ESG events in the company's performance. As Dorfleitner et al. (2020) argue, this information may improve the information efficiency of the market. They also point out, that noting absence of the controversial events can be beneficial for small companies, whose information is often overlooked and therefore incorrectly priced by the market.

The results of my investigation show that with the increase of ESG score, the probability of default also increases based on the data of the sample. The result is significant at 1%-level in both fixed-effect regressions: 1) only year-effect is fixed, 2) only firm-effect is fixed. And although the correlation between the probability of default and ESG scores in my sample is negative (note, not statistically significant), the multiple regression results suggest a positive relationship between these two variables. This supports my first hypothesis – the ESG scores may be increasing the probability of default, which could be explained by the agency theory. On the other hand, ESG Controversies scores have negative relations with the probability of default, the result is significant at 1%-level when the year-effect alone is fixed.

The endogeneity concerns, full exploration of which lies beyond this research, have been partially eliminated by controlling for fixed effects and including control variables. Although some studies do not account for it or find no evidence for reverse causality in the case of sustainability and corporate financial performance, it should still be noted that reverse causality is possible between the probability of default and higher ESG activities, and research focusing on this matter is needed.

5.1 Limitations and future research

Potential future research could be focused on the analysis of the relationship between separate ESG-pillars and default risk. The risk, on the other hand, can also be broken down into the systematic and idiosyncratic risk and the effects of the ESG activities analyzed separately.

Another limitation of my study lies within the fact that the ESG scores in the Refinitiv database are only "definitive" for the years prior to the past five years, which means that corrections can be added for the past five years' data points in case of the company's restatements or changes in the underlying data (Refinitiv, 2021). This means that in case someone would like to collect the same data for the same sample as mine, they will not necessarily match, if the five years have not yet passed.

Baghdadi et al. (2020) investigate endogeneity concerns in their work, which seems reasonable to investigate the ESG-EDF relationship as well. It is not clear at this point whether the increasing ESG-activities of the firm increase the probability of default or the firm with an increasing probability of default is trying to perform on the ESG-activities because of that.

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Appendix

Variable definitions

Amihud	Amihud measure of illiquidity. Annual average of the daily ratio of the absolute value of stock return divided by dollar trading volume, multiplied by one million as per Amihud (2002).
Annual return	The firm's annual stock return is calculated from monthly returns over the previous year.
EDF	Expected default frequency, calculated as N(-DD), where DD is distance-to-default, which is calculated following Merton (1974) and Bharath and Shumway (2008), and N(.) is the cumulative standard normal distribution function.
ESG_score	The ESG score was obtained for each firm-year from the Refinitiv Database. For more details on calculating the score, refer to Refinitiv (2021).
ESG_contr	ESG controversy scores were obtained from the Refinitiv Database Refinitiv (2021).
Equity	The market value of equity in EUR is calculated as the product of a number of shares outstanding and the stock price at the end of the year, both obtained from the Refinitiv Database.
Excess return	Annual excess return is the difference between the firm's annual stock return calculated from monthly returns over the previous year and return on the CRSP value-weighted index over the same period.
Debt	Face value of Debt in EUR calculated as the sum of short-term debt and one-half of long-term debt, both obtained from the Refinitiv Database.
σ_E	Stock return volatility, i.e. annualized standard deviation of returns, estimated from monthly stock returns over the previous year. Returns obtained from the Refinitiv Database.
ROA	The ratio of net income to total assets, both obtained from the Refinitiv Database.